Multicomponent Robotic Systems and Hybrid Intelligent Systems, a Path to Autonomy

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Abstract. The area of cognitive or intelligent robotics is moving from the single robot control and behavior problem to that of controlling multiple robots operating together and even collaborating in dynamic and unstructured environments. This paper introduces the topic and provides a general overview of the current state of the field of Multicomponent Robotic Systems taking into consideration the following essential problem: how to coordinate multiple robotic elements in order to perform useful tasks. The review shows where Hybrid Intelligent Systems could provide key contributions to the advancement of the field.

Keywords: Intelligent robotics, multi-robot systems, modular robotics.

1 Introduction

The classical concept of general purpose industrial robot, both in the case of manipulators and mobile robots, makes sense when the task to be carried out takes place in static or controlled completely structured settings. However, when the environments are highly dynamic and unstructured and when the tasks to be performed are seldom carried out in the same exact way, it is necessary to make use of robotic systems that require additional properties depending on the task. Examples of these environments are shipyards, plants for constructing unique or very large structures, civil engineering sites, etc. In these environments, work is not generally carried out as in traditional automated plants, but rather, a series of individuals or groups of specialists perform the tasks over the structure itself in an ad hoc manner. Consequently, it is necessary to seek new approaches based on design specifications such as modularity, scalability, fault tolerance, ease of reconfiguration, low fabrication and maintenance costs and adaptation capabilities that permit automating processes in this type of environments.

Thus, structures that can adapt their hardware and capabilities in a simple manner to the task in hand are sought. At the same time these structures, as they are designed for operation in dynamic environments, must be endowed with capabilities that allow them to adapt to their environment in real time. Obviously, they must continue to operate even when failures occur in some of their components, that is, they must degrade in a non catastrophic way. All of these requirements imply the construction of a modular architecture, a standardization of the interfaces between modules and an appropriate organization of perception, processing and control for these types of structures that implies the reconfiguration of the system in an intelligent manner for the completion of the mission.

All along the paper we use the notion of Multicomponent Robotic Systems (MCRS) which generalizes and refers to the diverse modular and multi-robot systems we are interested in. An atomic component of these systems will be referred to as an individual or module in the following. It can be a functionally complete robot unit or a module that needs to be combined with others in order to produce a desired functionality. We define the MCRS as a set of individuals with a superimposed architecture. This architecture consists in the definition of a spatial distribution for the individuals, a set of local and global control algorithms, and communication means and protocols for transferring information among individuals. When we talk of global conditions or properties, we are referring to the whole set of individuals, whereas local conditions and properties refer to the isolated individual. In the following we will review some ideas that will set the stage for the discussion on the application of Hybrid Intelligent Systems to this type of structures.

Hybrid intelligent systems are characterized by the composition of the different available computational tools (Bayesian reasoning, neural networks, fuzzy systems, statistical classifiers, evolutionary algorithms, etc.) in a way that is adapted to the particular problem to be solved. They are aimed at achieving the highest degrees of flexibility and adaptation. Until now, most MCRS are characterized by the simplicity of their control systems, which are often handcrafted for the particular task that must be demonstrated. We believe there is an open wide application field for hybrid approaches to this type of systems.

Throughout the paper we will consider MCRS from several key points of view, relating to the state of the art and trying to identify relevant Hybrid Intelligent Systems based avenues for research. The paper structure is as follows: in section 2 we will review some desired properties for MCRS. Section 3 will deal with the coupling among individuals. In section 4 we will consider the morphology of systems and individuals. Section 5 is devoted to the implications of the environment and the task definition. Section 6 discusses control issues. Section 7 refers to perception. Finally, section 8 summarizes our conclusions on the avenues of research for Hybrid Intelligent Systems in MCRS.

2 Some desired properties of MCRS

MCRS must be endowed with specific properties that will permit performing tasks that no individual robot may carry out by itself or to perform them with increased efficiency and economy. As an extreme case in warehousing systems, a swarm of robotic units may allow scaling the input/output capacity of the system. In this case the system is physically and functionally completely uncoupled, except for the need to avoid collisions and deadlocks. Another example is the ability of s-bots to arrange themselves in a configuration that may allow them to overcome obstacles such as trenches that cannot be overcome by an individual. More MCRS examples performing several tasks with diverse success degrees may be found in the literature. Our question here is: what are the properties that will distinguish a new MCRS generation? Let us briefly go through some of the most relevant.

Autonomous Reconfiguration: It is the ability of a system to modify the functional/spatial configuration of its individual components without external intervention. This property is the critical one in the present state of the technology. In current systems, the external (human based) interventions happen at two levels: reconfiguration process planning and decision on the need to perform the reconfiguration. Usually the determination of the goal configuration, and the computation of the sequence of intermediate configurations needed to reach this goal configuration are carried out outside the MCRS (in the sense that computations are not performed by any of the individual components), in some cases even the traction/actuator programming to perform the reconfiguration is an ad hoc program. The decision on the need to reconfigure implies the evaluation of the actual MCRS configuration relative to the assigned task and the state of the environment [91]. Nowadays in most systems this decision is not performed automatically, only some very low level tasks, such as pursuit, do not require a specification of this decision or the reconfiguration process [95]. Some autonomous reconfigurations in simulated systems has been reported using cellular automata [150], however the state of the art is very far from truly physical realizations.

The idea that robots should be able to self-configure is introduced in [86, 103, 104, 159, 176] over one type of modular robot, the M-TRAN [75, 85, 86]. In its current state of development the transitions between configurations are achieved manually and a few configurations for particular tasks are obtained through genetic algorithms and other global random search methods. To provide reconfiguration capacities implies two different types of problems. On one hand we have the processing problem of deciding how to get from the current configuration to the target one as a series of operations. On the other it is necessary for the hardware of the system to allow for reconfiguration. In the case of distributed robotic systems, to reconfigure is basically to change relative positions. However, in the case of modular robots, the different modules must couple and uncouple autonomously. Consequently, there is a need for specific hardware designs that allow for these actions and which involve the mechanical aspects of the coupling mechanism, its actuation systems and the design of the communication and powering contacts that allow for autonomous coupling and decoupling. The body of work on this topic one can find in the literature is very small and usually related to very simple toy systems. For instance, the idea of self-configuration over Yim´s polybots is proposed in [174]. For planetary robots Liping [89] proposes a coupling method that is based on position sensors and the work presented in [113] proposes another one based on magnetic couplings that may lead to new proposals of self-configurable robots. In terms of the processing problem, an area of active interest is that of the application of intelligent (hybrid) systems for the autonomous on line reconfiguration of this type of robots. It would really be necessary to reformulate the problem as a distributed optimization problem with partial information and combine estimation methods (Bayesian or neuronal approaches) with robust optimization methods (evolutionary or graduated convexity techniques).

Autonomy: It is a general property, which is desirable for any type of robotic system in all kinds of situations, but especially in unstructured dynamic environments. Autonomy implies that the system is able to adapt its configuration and perception and control systems to the changing environment conditions without human intervention. Autonomy implies life-long learning [18, 50, 54, 110]. It also implies self-sufficiency, meaning the ability to preserve its own life without external intervention (power and maintenance). It is also important to consider the autonomy of the individuals inside the system. In other words, it is convenient to examine how freedom degrees and responsibilities are passed down to the individual level when the whole system increases its autonomy.

Advanced Human Robot Interaction (HRI): This kind of systems must coexist and interact with human operators in the same environment. They must comply with security standards, and, consequently, deal with communications to/from human operators. Regarding communication, the focus is on the task specification problem. It would be desirable to have systems able to correctly interpret incomplete and imprecise specifications, as discussed above. Moreover, when embedded in unstructured dynamic environments, the robotic system will be required to guess the information needed to adapt the task specification to the current environment state. The HRI may imply multimodal signal processing (image, sound, gestures, etc.) [64], but at present the logical/symbolic process of ensuring that the task will be correctly performed regardless of its poor specification is of paramount importance. Another interesting feature of new generation MCRS will be their ability to autonomously perform the decomposition of the task according to its configuration, comprising the possible reconfigurations as a result of this task evaluation and decomposition. When considering cooperating systems, the task decomposition will be additive: The completion of the task results from the addition of the completed results of the subtasks. In the case of coordination, the task decomposition is additive along the time axis: there is a timing requirement or some kind of completion order for the subtasks. On the other hand, for competition, we assume a maximization process in which the same task is assigned to many individuals, which will provide the best result through competition, or the competition produces as a side effect some emergent behaviour that solves the task [149].

Self-perception: the system is able to determine (diagnose) its configuration from sensing or effector's information. It implies determining the relative positions of its robot units or modules, and their current functionalities.

Self-localization: the system is able to provide its spatial position as whole. It may imply the construction of a map of the environment [15], or simply the position of a single individual (such as the hose head in systems that transport hoses and are linked to them) relative to its desired position. The capability of simultaneous localization and mapping (SLAM) provides the maximum autonomy to the system [107, 128].

3 Coupling

Because this paper aims to deal with equivalent problems across the diverse types of MCRS, it is required that we define a parameter that will allow us to create a taxonomy of the different kinds of systems. This parameter is the degree of coupling among individuals and it characterizes the strength of their coupling. We distinguish between physical, functional and informational coupling.

By considering the gradation of the physical coupling, we can characterize some of the large groups of MCRS found in the literature. When there is no physical coupling we have an Uncoupled Distributed System. Examples are Robot Soccer teams [53, 72, 80], teams of UGV or UAV [123, 124], or uncoupled swarms [129, 148, 175, 178]. Within this category a lot has been written about robot swarms [43, 46, 153, 154] , that is, relatively large groups of robots that collaborate to achieve an objective, for example, rescue tasks [148, 149], material handling in flexible fabrication cells [45]. When there is a rigid physical coupling and it produces a new unit with new physical and functional properties we have what are generally called Modular Systems. Examples of these systems are the polybot [59], M-TRAN [86], Proteo [16], Uni-drive [76] or even, in some cases, the s-bots which can couple to perform some specific tasks [44, 84, 101, 102, 133, 162], being really a hybrid between a modular and distributed systems. Modular robots present structural degrees of freedom in order to adapt to particular tasks. One of the first practical implementations is a sewer inspection robot [32] although the idea of reconfigurable modular robots starts with the designs by Yim [164, 171-174] of a polypod robot that is capable of adapting its structure in order to produce different gaits for moving over different terrains. In [28] this philosophy is applied to the design of flexible fabrication cells. Finally, as a third category of systems, we can define that of the systems coupled through a passive non-rigid element. We call them Linked System. The prototypical case is that of hose manipulated by a team of robots attached to it, or grabbing it (without letting go, that is, the hose becomes a part of the robot system). This connection imposes constraints on the robot dynamics, which interfere in their coordination. It is also a non-linear transmission medium for the dynamical influences among robots.

It is important to note that MCRS are contemplated as a generic class of systems and our objective is to discuss ways of providing global autonomous actuation and reconfiguration strategies for them that permit the creation of heterogeneous robotic systems with any proportion of the three extreme types defined above and which delimit the domain (Modular, Linked and Uncoupled Distributed Systems). For instance, s-bots can act as uncoupled swarms and as modular systems [162]. As another interesting case, Continuum Manipulators [73] are a limit case of modular systems that become almost linked system. For illustration purposes, some examples of multicomponent systems that combine the three extreme types of system in different degrees are presented in figure 1.

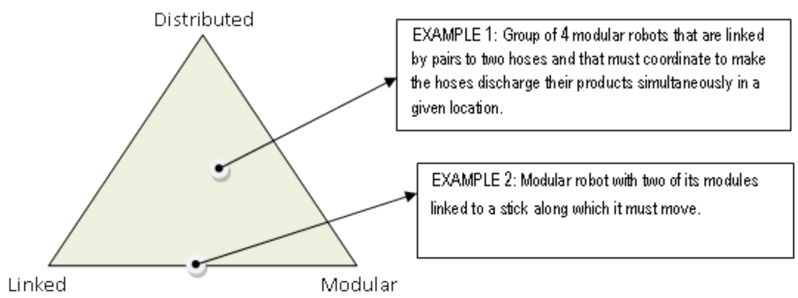

Figure 1 Instances of MCRS as mixtures of the elementary system types

The functional coupling degree deals with the level of functional dependence between individuals required for the MCRS to be able to accomplish an assigned task or function. This dependence manifests itself in several ways. It may be that the individuals need to be placed in precise relative spatial positions (with or without physical coupling) (i.e.: the composition of s-bots to overcome an obstacle), that they need to perform relative motions (i.e.: UAV trajectories for a given mission) or that the individual functionalities are applied according to a plan [91]. This logical dependence can be rigid (when the individuals must comply with a condition in an exact manner) o relaxed (when a range of variability or uncertainty is allowed). The system will be fault tolerant when it can accomplish its task/function regardless of the failures of individuals to meet their conditions (schedules). In general, it is essential to take into account the global system task/function to consider the functional decomposition and its assignment to the individuals. The problem of the functional dependence decomposition can be posed as Dynamic Programming problem, where the a priori knowledge about tolerances and uncertainties in the functional coupling must be dealt with by probabilistic or fuzzy reasoning methods [91].

The communications coupling is defined by the communications topology and protocol between individuals. The topology is given by the definition of the communications links and their properties (bandwidth, noise, persistency, delays). In some publications the communications coupling is identified with the system architecture, because it conditions the feasibility of distributed control, and the communications links may imply the existence of physical couplings o some spatial conditions (wireless coverage). For instance, the existence of communications delays implies dynamical effects on the design of the control system at the local and global level. In general, and even more for distributed control systems, it is desired that the communications topology be complete, that is, that each individual is connected to any other individual. A special case within this category are those systems whose communications link is through marks on the environment (stigmergy). Some authors have made use of this type of approach using the pheromone metaphor [19, 34, 115-117, 120, 136, 155], as in the case of ant colony algorithms. In this case the MCRS is structuring the environment to obtain some control effect.

It has been recognized that one of the critical aspects of this type of systems (Uncoupled Distributed Systems) is the communications between the members of the team [147]. It is usually carried out using radio-links whose robust behavior as communications links among the robots performing tasks has been a problem [47]. This is specially so when operating in real industrial environments performing real tasks. Take into account that industrial environments usually involve lots of machinery that introduce all kinds of noise in the communications channels. In addition, environments such as those relating to ship construction are metallic (steel plates) and consequently act as electromagnetic shields, hindering communications. Dongtang et al. [42] study the need of optical communications and evaluate a system based on photo sensors and laser as an alternative. In other cases, the communications task must become one of the "survival" tasks of the system and, as such, the system must introduce it within its behavior repertoire assigning resources for its implementation (units that act as messengers, the construction of opportunistic ad hoc networks, etc.). In fact, one of the problems in self-reconfiguring systems is how to correctly set up and maintain communications through morphological change or redistribution processes. Some work has been carried out in this line such as that in [57] where in the framework of modular robotics, the authors propose a hybrid communication system that can connect on-demand to form arbitrary network topologies.

Summarizing, MCRS may be classified along a coupling axis. This coupling may be physical, functional or informational based. The latter has to do with the need for communications in the joint operation of individuals in order to conform a successful MCRS. In this line, we can have from completely uncoupled systems that do not need to communicate to perform their tasks to very closely coupled systems that need to continuously and extensively communicate to be able to operate and many other instances in between with stigmergetic or explicit communications, with different channels and approaches to performing the communications process, including specific behaviors for communications. In terms of functional coupling, tightly coupled systems require very reliable and well defined operation of the individuals for the system as a whole to be able to operate. However, loosely coupled systems can tolerate errors or malfunctions in the operations of individuals and still perform the system task. Finally, in terms of physical coupling, we can distinguish among Distributed, Linked and modular systems.

4 Morphology

Robot shape determines its functionality, that is, the kind of tasks it can perform. In other words, the embodiment determines the intelligence of the robot. The tasks and functions that an individual may assume within the MCRS are conditioned by the morphology of its individuals and that of the whole. In the framework of a MCRS all the individuals may have the same morphology (homogeneous systems) or not (heterogeneous systems) [157]. The later may present the advantage of lower cost individuals and less redundancy in the functionality repertoire of the system. The former presents the advantage of independence from specific individual performance, because all the individuals are interchangeable and may assume all the required functionalities. This also implies an approach to implement better fault tolerance.

The MCRS morphology as a unit comes from the consideration of the system's configuration [119]. This is especially true for Modular Systems, where the physical coupling of modules produces a new unit with shape and properties that depend on the spatial configuration of the components. In uncoupled Distributed Systems, the individual's spatial distribution conditions some aspects of the system, such as the communications network and, in some cases, the degree of accomplishment of the assigned task [88, 96, 119]. In Linked Systems (hoses) the spatial distribution includes the passive link element and its physical properties, which may strongly condition the whole system behaviour.

The morphological design of the individual [76] determines the extent of the whole MCRS configuration space and its functionality. In the case of Modular Systems the emergent properties of a configuration usually allows performing tasks that the modules cannot perform. One of the current challenges is the optimal morphological design for the module in order to be able to produce some desired emergent properties [127]. Evolutionary algorithms, and other random search algorithms, have been applied to this endeavour in the framework of Evolutionary Robotics [105].

The work in [164] discusses the limitations of metamorphic robots based on cubic modules. Different modular configurations are being proposed even nowadays, examples are [24, 59, 62, 76, 160]. New classes of robots are introduced in [20] where Campbell et al. present robots that are configured as power buses while performing the assigned task. In [22] Carrino and col. present modules for the construction of feed deposition heads in the generation of composite materials. The works reported in [29, 139, 168, 170] study kinematic calibration methods and ways for obtaining the inverse kinematics and the dynamics of modular and reconfigurable robots in order to solve the problems introduced by tolerances in the fabrication of the modules. On the other hand, [17] presents a methodology for the dynamic modeling of multirobot systems that facilitates the construction of simulators to be used in order to accelerate the development of intelligent control systems through virtual experiments.

Regarding the automated design of modular robots, some work has been carried out in the application of evolutionary algorithms that seek the minimization of a criterion based on the variety of the modules employed for a given task that is kinematically characterized [169] or on the mass, ability and workspace [87]. In [180] Zhang and col. provide a representation of the robot and the environment that permits the application of case based reasoning techniques to the design of a modular robot. For the automation of the design of the configurations of modular robots, including self-reconfigurable robots, [79] proposes a representation of the potential connection topologies among the modules. Saidani [134] discusses the use of graph theory and cellular automata as a base for the development of design and self-reconfiguration algorithms.

Despite all of the activity along this line, research is mostly based on pre-designing systems and not really on their real-time redesign or adaptation to new components. This type of systems will not be really autonomous until these design and analysis tasks are carried out in an autonomous and distributed manner over the robot modules themselves allowing for real time reconfiguration of the modules when necessary. Again, robust estimation and modeling methods that are still not in general use are required as well as other hybrid techniques that will constitute some type of distributed cognitive mechanism for the MCRS.

5 Environment and tasks/activities

The environment is the operation ambient of the MCRS, also called the external configuration space. It encompasses the physical space as well as the diverse operational conditions on its performance, from electromagnetic noise interference on wireless communication up to illumination variations or the spatial distribution of obstacles. In a structured environment all the elements are determined within a known variability range. The system design and its human operator can trust this information. Moreover, the structured environment often helps accomplishing the task (i.e.: mobile robot navigation using floor printed paths/marks).

The environment for the robotic system may determine many of its design elements, for instance, a robot for operating in vertical surfaces [131] shows many specific traits non shared with other MCRS. The motivation and justification for the proposition of advanced robotic solutions lies in the assumption of new working environments, which do not offer favourable conditions for the robot operation, like very cluttered environments [138]. The environment may even impose conditions on the self-assembly process [61]. In unstructured dynamic environments, the knowledge about their shifting conditions is uncertain and the usefulness of any robotic solution is restricted in time. In the paradigmatic case of shipyards or civil construction sites, the environment is not suited for conventional autonomous robots and, on top of that, it is continuously changing as the construction proceeds toward its completion. So we have a non-stationary trend superimposed to the stochastic variations due to the normal operation in the environment. For static unstructured environments, an initial environment-scouting phase must be enough to build the map that would be used in the operation phase. The need of maps would be unavoidable in many tasks, where pure reactive behaviour would not be appropriate to accomplish them. For dynamic unstructured environments, there is an unavoidable need for regular monitoring looking for changes, and the systematic updating of environment information. Some kind of **life-long learning** is required to deal with this kind on environments. The previous problems can be basically focused like a merging problem the different maps created by each robot [2, 5, 15]. They can also be interpreted as a distributed AI problem where each agent carries out a part of the modelling task [55, 144, 158]. There are also approaches that include specific hybrid artificial intelligence methods for the environment model building [68, 181].

When we impose an objective to the robotic system we are assigning/defining it a task to be performed, i.e. target tracking, garbage collection, search, transport, coverage of an space, soccer playing, hunting, escorting [7, 12-14, 41, 44, 63, 66, 72, 78, 81, 106, 126, 132, 137].

Nevertheless, a system may show activity that does not address the satisfaction of an externally set objective. In other words, not all the activities of an MCRS necessarily serve the accomplishment of an assigned task; the system may be operating even when no task has been assigned to it. For instance, individuals may have inescapable needs (battery charge, environment map maintenance) that force them to maintain some activity. These needs can be understood as endogenous tasks.

Besides the uncertainty about the environment state, the task specification itself can be imprecise or incomplete. Imprecise in the sense that the goal is not precisely stated, (when a navigation destination is set relative to an undefined environment condition). The task can be incompletely specified in the sense that some situations are left unspecified. This situation may be the most common in unstructured dynamic environments. Some robust specification interpretation and evaluation mechanisms will be needed to cope with imprecise and/or incomplete specifications. The problems raised to achieve such ability offer a rich and unexplored avenue of application of Hybrid Intelligent Systems.

6 Control

Control is the system aspect able to produce a decision sequence that reach (or try to) a desired goal given some information about the environment and the system itself. The goal statement implies the definition of a task. The definition of control carries with itself the ideas of intelligence and optimization. Intelligence as the ability to plan an execute action sequences. The control process becomes fully or partially an optimization process as long as the stated goal can be formulated as the global extreme (maximum or minimum) of an objective function [105]. Obviously, if the system has some assigned task, this task determines the goal pursued by the control system. Additionally, we can find hierarchical or sequential task/goal decompositions, so that the local minimization performed by each agent contributes to the global optimum seeking process [98]. In unstructured and dynamical environments, control processes must be able to detect and also recognize variations taking place in the environment, in order to adapt the decision and planning processes [69]. The objective function can be the preservation of a relative spatial configuration [119] or the time to accomplish the task [66]. The uncertainty in the environment knowledge introduces uncertainty in the evaluation of the objective function and on the effect of the decisions taken as a result of its optimization. New optimization (i.e. evolutionary) algorithms dealing with imprecise, non-stationary or noisy objective functions may be useful in this setting. There are few instances of heuristic propositions of control strategies [143, 177].

For MCRS systems control is defined at two levels: the individual (actuator control) and the global system (mission control). The most substantial difference is that, often, global system goals are fixed from the task statement, in other words, the task is assigned to the global system. The individual's goals are, often, given from a competitive or cooperative [77, 119] decomposition of the task goal.

Probably the most interesting approach from the point of view of the industrial or real world applications is the one based on cooperative decomposition [77]. Cooperation may be used in order to achieve common goals, divide the tasks, which is sometimes based on task allocation algorithms, and load balancing, to avoid the conflicts while the task is accomplished, or to make a collective decision [10, 37, 50, 119, 123, 125, 126, 157, 158, 162]. Sometimes the basis for the cooperation is to obtain the maximum reward for the system as a whole. Usually theses cases are implemented by means of ant colony optimization (ACO) [27, 38, 182, 183] or reinforcement learning paradigms [9, 52, 71, 97, 156, 167]. On the other hand, the competitive approach is applied mainly when the roles of other environmental elements are taking into account as in the robot soccer [9, 53, 72, 80, 156], or when the system is inspired on a general multiagent system [71, 100].

It is important to notice that the global performance depends on the individual performance, which is especially true for cooperative task/goal decompositions. Individuals must be trustworthy in the sense that the global system can have confidence in them to accomplish their corresponding goals. Alternatively, the global system may be fault tolerant, achieving the global goals regardless of failure of individuals. Note that competitive systems will be inherently fault tolerant.

Another important distinction is that between centralized [13, 40, 66] and decentralized (distributed) [23, 35, 102, 109, 118, 119, 135, 136, 142, 145, 153] control schemes. In the former, a singular individual computes the task/goal decomposition, assigns them to individuals and maintains information about the global system progressing to the global goal. In the later, the global goal fulfilment emerges spontaneously (synergistically) from the independent fulfilment of the individual tasks/goals. Evidently, the individual tasks must have been formulated in an appropriate way and the global problem must be decomposable (a common research issue in agent literature) [50, 98]. This decomposition may be reach by negotiation like in [121, 135], or by some swarm dynamics [178]. The communication structure is intimately related to the control decentralization, but not necessarily determines it. For instance, it is possible to find decentralized control systems where, there is a central communication (broadcasting in some cases) node that performs only the role of intermediate relaying messages between individuals. The control scheme must take into account the communication structure (topology, noise, reliability), although there exceptional systems that accomplish cooperation without communication [130]. Decentralized control systems are expected to be more fault-tolerant.

The control schemes must maintain at every moment updated information on the environment state, the system's own state and the level of accomplishment of the task. There are two natural information levels in the MCRS: individual and global. In centralized control schemes the singular individual maintains the global information that supports/implements the central control. It is t that the fusion of local information takes place when required. In decentralized control schemes, the local information of each individual usually includes information generated by its own sensors and computational processes as well as an estimation of the local information in the remaining individuals, obtained from the communications received [178]. The study of consensus [123] heuristic algorithms and processes aims to establish the convergence of the local information under noise and uncertainty to a global precise picture of the whole system, environment and task state comparable to the one that a centralized controller can build with perfect information. They have been applied to mobile autonomous systems. Some authors emphasize the role of communication network as the key for distributed control system development and deployment. We single out [123, 124] which devote their efforts to distributed control of autonomous vehicles performing cooperatively and co-ordinately a task. Their central idea is the local estimation of a trustworthy local representation of the global system and environment states. The consensus building processes attempt to produce this representation in a robust way from the communication among individuals. Control of heterogeneous groups of robots may need the coexistence of heterogeneous control rules (set at the start) at the individual level [157] and the coordination between the different groups as a whole.

Some Modular Systems are better suited to be controlled in a feedforward way by pattern generators, that can be hybridized with neuronal structures such as the ones in [70, 93, 99], in fact the M-TRAN self-reconfiguration is performed by a Central Pattern Generator and a Genetic Algorithm [86]. Due to the inherent nature of this problem, it is very usual to find biological inspired approaches for controlling the movements of this kind of robotic mechanisms [90, 140, 146, 179]. Usually they use any kind of hybrid approaches in order to generate locomotion patterns to be applied to the mechanisms.

New hybrid approaches for distributed control may be inspired by the hybridization of reinforcement learning with evolutionary algorithms [94], but also by most classical mixtures of declarative, procedural knowledge and case based reasoning [152]. The enrichment of the situational calculus in [53] with other computational intelligence tools, may enable this approach to extend to very unstructured dynamic environments. Distributed Control can be also obtained evolving fuzzy [163] or neuronal [72] controllers that exhibit some emergent behaviour. Many design tasks fall in the field of Evolutionary Robotics, as they can be formulated as minimization of a given objective function [43, 105].

The biological foundations of the idea of robot swarms are reviewed in [155], including a prospective of their application in [132]. In [56] Fukuda and col. discuss the advantages and disadvantages of multiagent robotic systems as compared to single robots. The individuals considered are in general very simple in their internal dynamics and, consequently, the introduction of sophisticated approximate reasoning systems would permit an extension of the range of behaviors and their robustness to changing situations.

In [118] Peleg presents a universal architecture for the decentralized control of groups of robots. A review of the state of the art of decentralized control is given in [142]. Wessnitzer and Melhuish [166] integrate behavior based control strategies with swarm control systems in a task having to do with the elimination of underwater mines. Dorigo, within his swarmbots project [44] presents a hunting behavior as a collective decision making process. In general, the formulation of decentralized control implies the need to work with incomplete or temporally inconsistent information. Hybrid intelligent systems should help to improve the robustness of these control systems.

7 Perception

Perception is inherent to any robotic system in order to obtain feedback information on the effects of the decisions taken and the actions performed. Perception subsystems include the sensors as well as the computational processes (filtering, feature extraction, encoding) that produce the information as will be used by the control schemes [48]. Sometimes, perception is the driving task [125] for the MCRS behaviour. Robot perception has two aspects, the perception of its own being (propioception in biological systems) which we call self-perception and some authors call self-recognition [58], and the perception of the environment.

Map building is an essential perception process in many applications [2, 5, 30, 55, 68, 125, 158, 161, 165, 181]. For instance, in [84] Kumar and Sahin consider the problem of generating cognitive maps in mine detection. Pack and Mullings [109] introduce metrics so as to measure the success of a joint search performed by a swarm as well as a universal search algorithm. There are a variety of techniques that have been used to perform this task with distributed multi-robot systems, from occupancy grids [2], Genetic Algorithms [181], Morphological Neural Networks [165] and Particle Filters [68]. The maximum expression of autonomy is the ability to perform autonomous simultaneous mapping and localization of the robot units (SLAM) [11, 37, 39, 49, 161, 165]. This is a promising avenue of research where hybrid algorithms can be useful to perform more efficient explorations and feature extraction algorithms. There are already some hybridizations of Kalman Filter approaches with Fuzzy Systems for single mobile robots in environments that do not fit easily in the linear modelling paradigm [1, 26, 33, 67, 111, 112, 122].

A part of the life-long learning processes required for systems embedded in unstructured dynamic environments consists in the adaptation of the perception subsystem. This adaptation ranges from the need to operate robustly under changing sensing conditions (i.e.: changing lightning conditions for optical cameras) up to the need to discover new semantics (new objects or structures in the environment). Quantization and codification are the ways to assign meanings to the sensor data, to discover and identify information quanta equivalent to semantic concepts. Quantization partitions the data space to obtain a dimensional reduction or to remove uncertainty and noise. The association of discrete values to the partitions produces a data encoding. This data encoding allows translating the sub-symbolic data into the symbolic domain. Most of the adaptation processes in the perception subsystem consist of learning processes performing training of supervised and unsupervised quantizers/encoders, with some life-long learning versions for dynamic environments. Artificial Neural Networks architectures [3, 4, 51, 141] provide on line clustering techniques that perform this life-long learning process. New proposals for quantization techniques lie in the frontier between the already established computational domains of Artificial Neural Networks and Fuzzy Systems [60].

In MCRS some or all the individuals may carry out perception tasks. The fusion of the local perceptions (views) produces global information that can take the shape of environment maps [125] or other kinds of sensorial maps, some times modulated by attention processes. This fusion process can be modelled as multi-agent system [114] and may involve different sensors, that is, we may need to organize the sensing of the robot so that the different sensors are integrated in order to obtain the desired information. A primitive example is the application of Bayesian decision theory for door detection as presented in [83]. A decentralized Bayesian decision algorithm that may be used for the fusion of sensorial information in sensor networks is introduced in [92]. Kalman Filters have been applied with some success to this problem [6, 8, 21, 25, 36, 65, 67, 74, 108] in the context of SLAM. Hybridization of the Kalman Filter approaches with Bayesian, Fuzzy or Neural Network approaches may give interesting avenues for research.

In MCRS self-perception implies the estimation of the spatial configuration of the components. In Modular Systems, accounting for the module connections and the odometry of attached actuators may be enough to build an accurate representation of the system configuration. For other kinds of systems, self-perception may imply processing sensorial information, like recognizing identifying flags or symbols attached to individuals [82, 95, 123]. For uncoupled Distributed Systems the individual component position estimation may be done in a centralized (such as the zenithal cameras in Robot Soccer matches) or distributed way, when each individual recognizes other individuals belonging to the system and locates them. For Linked Systems self-perception implies modelling and parameter estimation of the passive linking element among robotic units, on top of the estimation of the individual robotic unit position. This process would be realized in centralized or distributed ways, by means of some consensus heuristic [123].

Finally, a very interesting form of control is that of sensori-motor maps, usually implemented through Artificial Neural Networks [93], these maps provide fast trainable reactive responses, and can be mixed with other control loops. An interesting application is that of positioning and map generation through robot swarms [128]. A precedent may be found in [31]. In the same vein, but at a higher cognitive level, Stroupe and Balch [151] try to estimate the best next move of a group of robots in order to obtain the map.

Summarizing, perception subsystems involve computational processes that require adaptability and life-long learning abilities for increased system autonomy. They still offer challenges to develop new intelligent algorithms. Many current perception subsystems employ computational techniques based on variations of Kalmann Filters, offering a wide spectrum of hybridization combinations.

8 Conclusions

We have introduced some of the current issues of the field of Multicomponent Robotic Systems trying to show where the Hybrid Intelligent Systems could provide interesting contributions to the field. Basically we have focused the fundamental problem of how to coordinate multiple robotic elements in order to perform useful tasks. After an initial statement on the desired properties that every MCRS should posses, we have dissected the main topics of this scope which integrate the coupling among the system elements, the morphology of the whole system and also of its individuals, the implications of the environment and the task definition, and how and where the control of this kind of systems takes place.

A broad spectrum of potential applications of Hybrid Intelligent Systems has become evident from this analysis. Algorithms are needed for the identification of the current state of the system, and to decide its actions,[68] in a collective distributed way, including the need to reconfigure the system. It is also necessary to develop efficient planning algorithms for the reconfiguration of a wide variety of systems, ranging from modular to uncoupled ones. New techniques for morphological design may allow to fit individual morphologies into the global functionality required to perform an assigned task. There is a systematic need of working with imprecise and incomplete information that may be temporally inconsistent that is detected when contemplating distributed implementations of control and sensing. Sensor fusion, whether from several sensors from the same robot or from different robots, requires robust and efficient modeling techniques.

Thus, as a final comment, we must say that the quest for Multicomponent Robotic Systems that are useful for applications in real unstructured and dynamic environments is still in its beginnings. Even though there has been a lot of work carried out in the last decade in this line, there is still a lot more left for these systems to achieve industrial level performance. This quest must necessarily involve an increase in the operational autonomy of the systems and we believe that one of the most promising paths to this objective is through the application of Hybrid Intelligent Systems based techniques.

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